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DOI
10.1016/j.energy.2021.120356

Publication date
2021

Document Version
Final published version

Published in
Energy

Energy 227 (2021) 120356

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Off-grid solar charging of electric vehicles at long-term parking locations

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A R T I C L E I N F O

Article history:
Received 27 August 2020
Received in revised form
25 February 2021
Accepted 6 March 2021
Available online 25 March 2021

Keywords:
Solar
Electric vehicle
Charging
Off-grid

A B S T R A C T

This work analyses the effectiveness of an off-grid solar photovoltaic system for the charging of electric vehicles (EVs) in a long-term parking lot. The effectiveness of charging is investigated through analysis of the states of charge (SoC) at departure of EVs plugged in at the parking lot over the simulated year. Although the share of vehicles leaving with inadequate charge over the entire year is small, this share is relatively high during low irradiance winter months. We show that an increase in efficiency of the solar modules used in the system and an increase in the minimum duration of time spent at the parking lot are effective within limits at improving charging adequacy. We then formulate three strategies to allocate the available energy in the system with the objective of reducing the number of vehicles leaving at lower SoCs: 1) curtailment of charging beyond 80% state of charge, 2) prioritised charging of vehicles at low SoCs and 3) prioritised charging based on both SoC and time before departure. We identify the strategy prioritising vehicles with low state of charge to be most effective, but performance in the worst month remains a challenge for the location considered.

1. Introduction

The global uptake of electric vehicles (EVs) is rapidly increasing, reaching a worldwide market share of 2.6% in 2019 [1]. The increasing consumer and public spending on EVs in combination with the increasing market share show a trend towards the electrification of the mobility sector. Electrification of mobility is also desirable from a climate perspective in locations like Europe where the electricity mix has a relatively low carbon intensity [2].

Larger EV fleets lead to an increase in the demand for both electricity and EV charging infrastructure. Providing infrastructure for the charging of electric vehicles at public locations is a key enabler for electric vehicle uptake and is essential for their widespread adoption [3]. However, considerable capital costs are involved in the installation of large scale charging infrastructure, particularly where there are clusters of charging stations [4]. As much as 20% of the initial costs and 35% of annual non-energy related recurring costs are associated with the provision of grid capacity [5]. Further, in many locations, capacity constraints in existing distribution level infrastructure prevent the connection of additional electrical load.

This work analyses an off-grid solar photovoltaic (PV) system for charging EVs plugged-in at long-term parking lots. These parking lots, where vehicles are parked for long durations (typically more than 24 hours), are often found in airports, ports and logistics hubs. The proposed system would have the following benefits:

1. The elimination of the grid capacity would lead to significant reduction in the capital costs of installation of EV charging infrastructure.
2. With the falling costs of electricity generation through solar photovoltaics, local generation would reduce the energy-related costs of providing electric vehicle charging.
3. EV charging would become possible even at locations without (or with a highly constrained) grid infrastructure.

We model a solar parking lot with 100 parking spaces, which are covered with solar modules, located at the city of Lelystad, the Netherlands, the site for a new airport. The generation of electricity through the photovoltaic array is simulated over a year together with the arrival and departure of battery electric vehicles (BEVs) which are charged in the parking lot. The operation of the parking lot over a year is simulated to estimate the adequacy of charging of

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https://doi.org/10.1016/j.energy.2021.120356

Abbreviations

AC	Alternating current
BEV	Battery Electric Vehicle
CR	Critical Ratio
DC	Direct Current
EV	Electric Vehicle
PV	PhotoVoltaic
PVGIS	PhotoVoltaic Geographical Information System
SoC	State of Charge
TMY	Typical Meteorological Year

EVs using the off-grid solar PV system. Various measures are then proposed for improving the adequacy of charging of the EV fleet and they are compared.

Several previous works have investigated solar charging for electric vehicles. Birnie [6] recommended locating solar arrays at workplaces due to the temporal overlap between charging in the daytime and peak solar generation. The daily energy generated was estimated to be sufficient for the range covered by most commuters within the 15–20 mile radius of their workplace. The insufficiency of generation in winter was acknowledged but not elaborated upon.

Denholm et al. [7] extended the idea of solar charging at workplaces. A modest PV capacity at workplaces in Texas was found to reduce the need for the additional grid capacity required for workplace EV charging by shaving of demand peaks. Workplace EV charging was also found to increase the utilisation of low value and potentially curtailed solar production in summer.

Additional benefits gained by co-location of solar arrays and EV charging related to carbon emission reductions and socio-economic aspects were described in [8] and [9]. The technology of solar carports was reviewed in [10] while the techno-economic feasibility of a system in Lisbon, Portugal was analysed in [11]. All these studies focus entirely on grid connected systems located at workplaces. As such, the assumption was that vehicles would be available for charging for a period limited by an average workday of around 8 hours. Alternative locations with different parking profiles were not explored.

Tong et al. [12] modelled an off-grid solar workplace charging station based on a single vehicle system built at the University of California, Davis, USA. The system included a 1.44 kWp solar array over a single carport with a 13.9 kWh second-life Li ion battery pack for stationary energy storage. For conditions in California, the system was found to completely charge the daily energy demand of the plugged in EV (10 kWh) for 194 days in the year. The battery was found to be highly underutilised in winter since there was rarely enough solar energy with which to charge it sufficiently. The authors did not, however, further quantify or address the effects of inadequate charging of EV batteries by the proposed system. Although increasing the stationary battery pack capacity was investigated, it was not found to improve system performance greatly. Further, no recommendations were made for alternative applications of the off-grid solar parking lot. Bhatti et al. [13] reviewed solar photovoltaic systems for EV charging, with a focus on power converter design. Converter designs for use in off-grid photovoltaic charging systems were briefly discussed, though specific applications were not investigated.

Chandra Mouli et al. [14] analysed the system design of a workplace parking lot for grid-connected EV charging in the Netherlands. Increasing the capacity of stationary batteries was investigated to reduce the dependence of the system on the grid for delivering adequate charging to the plugged in vehicles. Even extremely large battery packs per carport, with similar capacity as the batteries in EVs themselves, were unable to completely eliminate the reliance of EV charging on electricity from the grid for adequate charging.

Off-grid solar powered systems for charging electric vehicles including electrolysers for hydrogen production, local hydrogen storage and fuelling of hydrogen fuel cell electric vehicles were analysed in both [15,16]. Since electrolysers and fuel cells were included in the charging stations in both cases, long-term storage of energy was possible in the form of hydrogen. Although neither study explicitly looked at adequacy of charging of the vehicles, the energy provided by the off-grid system appeared to be inadequate since both works also incorporate backup diesel generators. Regardless of the nature of storage, whether batteries or hydrogen, the off-grid solar system was unable to independently and adequately meet the EV charging demand at workplaces.

Most solar EV charging studies tend to focus on workplaces, due to the temporal match between charging profiles and peak solar production. The analysis of alternative load profiles for EVs, with lower charging demand, is lacking. In this study, we focus on a novel profile found at long-term parking locations. These are parking lots where vehicles are parked for long periods of time, typically on the order of days to weeks. They can represent large shares of parking facilities. For example, at most airports, long-term parking lots serve about 25% of parking facility users, but occupy up to 90% of parking spaces [17]. The charging speeds required for EVs are expected to be considerably lower at long-term parking than those at workplaces, where the durations of parking (around 8–9 hours) imposes a requirement on the speed of charging. As such, both the daily energy demand and peak loads are lower. This suggests that off-grid solar systems are better suited for these profiles than for workplace load profiles. To the best of the authors' knowledge, this is the first work to analyse such a system.

The main research question that this work aims to answer is:

To what extent is an off-grid solar array suitably sized for a long-term parking lot able to meet the charging demand of plugged-in EVs? with the following sub-questions:

1. What is the distribution of SoCs achieved by the vehicles using the system and how many vehicles are inadequately charged?
2. How can the charging facility be better designed to improve the adequacy of charging provided?
3. What kind of smart approaches can be used to improve the adequacy of charging provided and what additional data is needed?

The contributions of this work in the context of previous literature are listed below:

1. In this work, we analyse EV charging profiles at long-term parking lots - a type of load profile that previous works have not investigated.
2. We develop a method where the adequacy of charging is analysed through the distribution of states of charge of EV batteries on departure. This differs from studies which use the more conveniently measured quantity of average daily electricity charged per charge point (termed as success of public charging stations, for further details refer [18]).
3. The techniques used for assigning priorities for vehicles here are derived from queuing theory. Conventionally, such techniques were used to analyse server-customer systems with applications ranging from communication networks to logistics management. They have found recent application in EV charge scheduling. For example, they were used in [19] to reduce cost of EV charging while in [20] they were used to analyse the

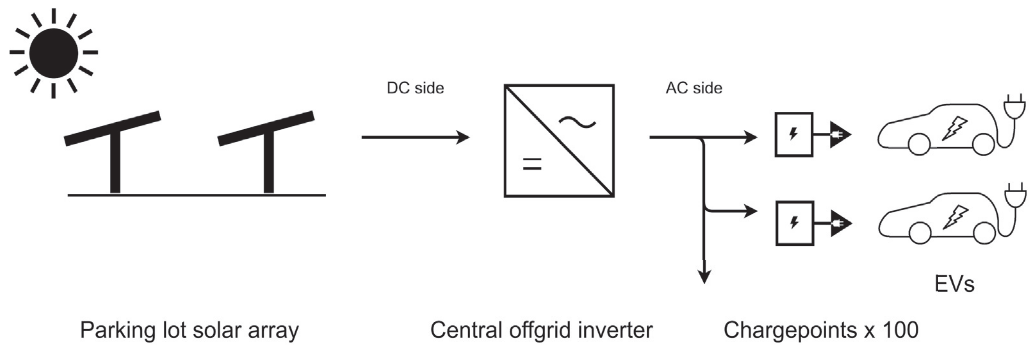


Fig. 1. System schematic of an off-grid solar parking lot for EV charging.

performance of charging EVs in various configurations. To the best of our knowledge, this is the first work to apply these techniques to EV charging in off-grid systems and compare various strategies using them.

The paper is structured as follows: in section 2, the physical system is described, together with the modelling of individual components and an overview of the data used for simulations is provided. In section 3 we describe the formulation of the base case and the adequacy of charging of EVs using the parking lot over a year. The performance during the critical periods in winter and the sensitivity of the results to design parameters is analysed. In section 4, we formulate and compare various strategies to improve the adequacy of charging for the EV fleet through prioritised charging. Finally, in section 5, we present the conclusions of this work and a few ideas for future research.

2. System description and data used

The system considered is an off-grid solar parking lot with 100 parking spaces located at the long-term parking facilities at the airport in Lelystad, the Netherlands. Relative to the total number of parking spaces available at most airports,[1] this represents a small fraction. We assume every parking space to be covered by a solar canopy and to have a charge point for EV charging. A schematic of the proposed system is shown in Fig. 1.

2.1. Solar PV array and inverter

The minimum ground coverage area per parked vehicle is taken to be 12.5 m^2 based on Dutch regulations for covered parking spaces [22]. Based on a conventional 60-cell module area of 1.6 m^2 and a low tilt, this gives a ratio of 10 solar modules per parked vehicle. A central grid-forming inverter is chosen rather than a modular system primarily to enable the electricity generation from unoccupied parking spaces to be used to charge EVs in occupied spaces. Further details on the PV array and inverter specifications are provided in Table 1.

Satellite derived irradiance and meteorological data for the site location is sourced in the form of Typical Meteorological Year (TMY) files from the Photovoltaic Geographical Information System (PVGIS) online tool [25]. We model the electricity production of the solar array over a year in hourly timesteps using the open source tool PVLIB version 0.7.2 in Python [26].

[1] Large airports have parking capacities in the range of several tens of thousands of parking spaces [21].

2.2. Charge points

The charge points considered are single phase alternating current (AC) charge points with 16 A current capacity. They are thus limited to 3.7 kW power capacity. The losses in the charge points as a result of charging are taken to be 0.3% [27].

2.3. Electric vehicles and their batteries

The vehicles being charged in the parking space are assumed to be similarly distributed as the top ten models in the current Dutch EV fleet. Only battery electric vehicles (BEVs), which generally have larger batteries than plug-in hybrid electric vehicles (PHEVs), are considered in order to test the limits of the system. Since range anxiety is typically not a consideration for PHEV drivers, it is debatable whether they would choose to charge their vehicles at such a location - another reason for their exclusion from this study.

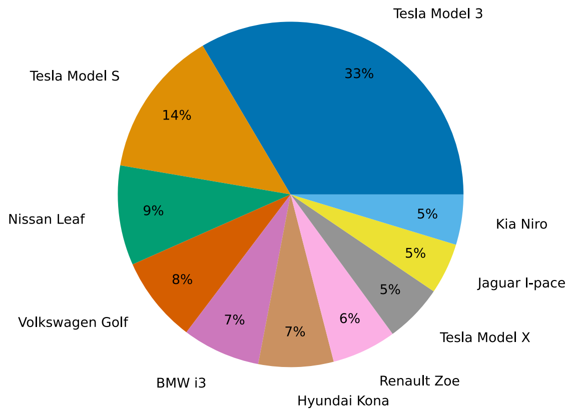
The BEVs considered range from the 32 kWh Volkswagen Golf to the 95 kWh Tesla Model 3 and Model X. Data on battery sizes is sourced from the EV database [28] while the distribution of vehicles is based on Dutch government statistics [29]. The distribution of vehicles is shown in Fig. 2(a).

The distribution of initial states of charge of the vehicles when plugging in at the solar parking lot is based on data collected in the EV Project. The dataset provides BEV battery SoCs at the beginning of charging sessions at away-from-home locations, collected over charging events across several years from over 5000 BEVs [30]. Fig. 2(b) shows the normalised distribution of initial states of charge of all the vehicles - a Gaussian distribution around a mean of 50%. Datasets from other EV trials in the UK [31], Australia [32] and Germany [33] across a variety of charge point locations show similar distributions of initial SoC at the point of plug-in.

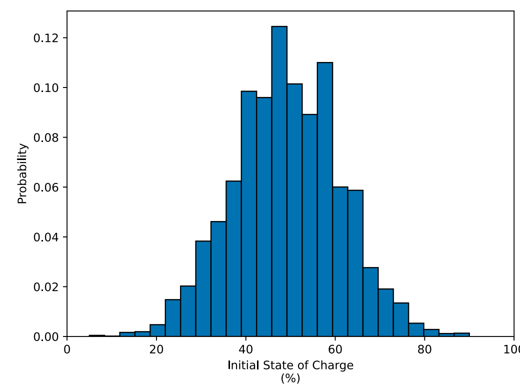
The charging of EV batteries is modelled using the Modified

Table 1
Solar array and inverter characteristics.

Characteristic	Value
Site location	Lelystad, the Netherlands
Site latitude	52.4° N
Site longitude	5.5° E
Solar modules per parking space	10
Number of parking spaces	100
Module technology	Crystalline silicon [23]
Module rating	320 Wp
Module efficiency	19.2%
Total installed capacity	320 kWp
Array azimuth	South
Array tilt	15°
Capacity factor	8.9%
Inverter efficiency	98% [24]



(a) Distribution of Vehicles



(b) Distribution of initial SoCs

Fig. 2. EV distribution and initial States of Charge on arrival.

Kinetic Battery Model [34], based on which the states of charge (SoC) of individual EV batteries are calculated. It is a commonly applied battery model used in time series energy system modelling [35–37]. It is an analytical battery model based on chemical kinetics, using battery datasheet values to approximate charging and discharging behaviour with relative accuracy [36].

2.4. Vehicle occupancy at the parking lot

The arrival times and durations of stay of the vehicles considered in this study are based on data collected at the economy long-term parking lot at Boston Logan International Airport. The two datasets used are.

1. time series data showing the number of vehicles entering a specific parking lot at an hourly rate over an entire month in August 2016
2. distribution of the total number of vehicles based on the time spent in the parking lot

Research studies conducted at airports around the world show segmentation of parking visitors based on duration of stay into short term, long-term, meet and greet, etc. [17,38]. Typically, the shares of parked vehicles in different segments are found to vary, but the common characteristics within each segment remain similar [39]. Thus, although we cannot explicitly demonstrate that patterns specific to the segment of long-term parked vehicles which are analysed here are representative of those at other locations, we assume this to be the case.

Daily and weekly seasonality can be seen in the vehicle entry time series data, based on which seasonal indices are calculated. The vehicles are then assigned durations according to the distributions of the vehicles parking durations in the data, with a minimum duration period of 24 h. The arrival rate is then scaled to limit occupancy of the parking space to 100 spaces. Fig. 3(a) shows the distribution of durations spent by vehicles in the parking lot over the year while Fig. 3(b) shows the occupancy in the parking lot over the year.

In large parking lots, it can be difficult to find the last parking spaces. Hence these parking lots are typically considered to be full when 85–95% of spaces are occupied [40]. In this context, the occupancy considered here is relatively high.

3. Immediate charging of the off-grid fleet

The time series data from the solar array, together with the EV occupancy is used to simulate the operation of the system over a year. As a base case, immediate charging is used to estimate the adequacy of charging of the EVs using the parking lot.

3.1. Formulation of immediate charging in the off-grid solar system

Let I be the total number of EVs using the parking lot over the year and J be the total number of charge points in the system[2] over the considered time interval, 1 … T. The i^{th} vehicle enters the parking lot at t_i^{entry} and exits at t_i^{exit}, remaining at the parking lot for a plugged-in duration of $D_i = t_i^{exit} - t_i^{entry}$. At any given timestep, $t = n$, the number of vehicles in the parking lot i.e. its occupancy, I_n, is known. Let $\overline{I_n}$ be the set of I_n unique values of i at the timestep n, which represent the set of identities of vehicles in the parking space at n.

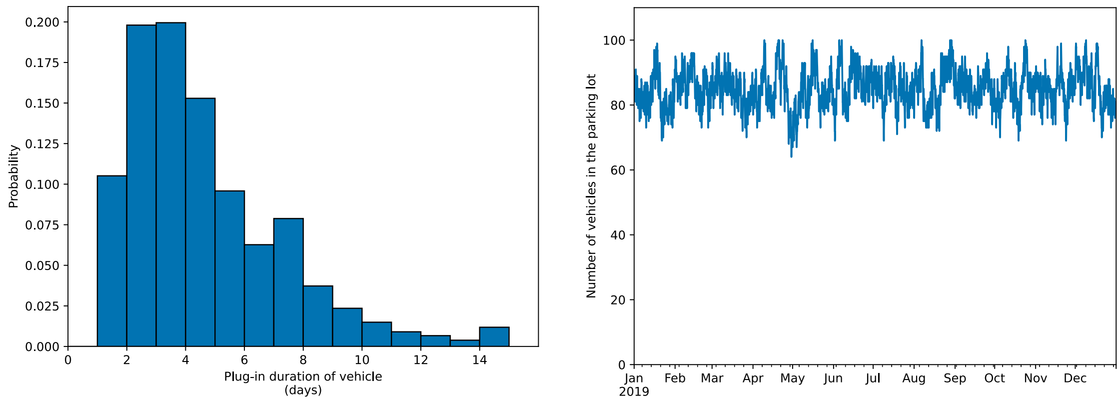
At any given timestep, n, the State of Charge (SoC) of the i^{th} vehicle is $S_{i,n}$. When the i^{th} vehicle arrives in the parking lot, i.e. $n = t_i^{entry}$, its state of charge, $S_{i,n}$, is known. At all other timesteps, it is a function of the charged power to the vehicle.

The power capacity constraint of every charge point is C. The time varying SoC dependent charging power capacity of the battery of the i^{th} vehicle at the timestep, n, is denoted by $c_{i,n}^{SoC}$ and is set by the battery model. At every timestep n, the power capacity of the i^{th} plugged-in EV, $c_{i,n}$, depends on the minimum constraint set by the charge point and the battery. Thus, for every timestep the power capacity of the i^{th} plugged in EV is

$$c_{i,n} = \text{minimum}\left(C,\ c_{i,n}^{SoC}\right) \tag{1}$$

If there were no constraint on the available electricity, each vehicle would charge at the limit of its capacity, $c_{i,n}$. However, in cases where the available power is limited by the solar array production in the n^{th} timestep after losses, P_n^{PV}. Thus, at each timestep, n, the total power charged to the plugged in fleet, is

[2] J also equals the number of parking spaces.



(a) Distribution of plug-in durations of vehicles

(b) Occupancy in the parking lot

Fig. 3. Distribution of plug-in durations and occupancy in the parking lot.

$$P_n^{fleet} = \sum_{i \in \overline{I_n}} P_{i,n} = minimum\left(P_n^{PV}, \sum_{i \in \overline{I_n}} c_{i,n}\right) \tag{2}$$

The power charged to the i^{th} vehicle is then calculated as

$$P_{i,n} = \begin{cases} c_{i,n}, & P_n^{fleet} \leq P_n^{PV} \\ \dfrac{P_n^{PV}}{P_n^{fleet}} \cdot c_{i,n}, & P_n^{fleet} > P_n^{PV} \end{cases} \tag{3}$$

Thus, in case of constrained power, charging of all vehicles is curtailed by the same fraction. The battery model is then used to calculate the SoC of each vehicle after charging.

3.2. Adequacy of charging

The objective of the system is to provide adequate charging to as many vehicles as possible. We investigate this idea of adequacy of charging by analysing the SoCs of all the EVs at their respective times of departure over the simulated year.

The solar production over the year and the power charged to the fleet are shown in Fig. 4(a). Considerable excess electricity is generated, which needs to be curtailed in summer months.[3] On the other hand, the solar yields in winter are far lower and restrict the charging of EVs considerably. These figures reveal that the provision of adequate charging to the plugged in EVs has a clear seasonal dependence.

The states of charge of all the vehicles at the point of departure from the parking lot over the year are shown in Fig. 4(b). Almost all the vehicles charged in the summer months are fully charged by the time they are required to depart. On the other hand, in the winter months, most vehicle are only partially charged, leaving with a lower SoC. A relatively low number of EVs in winter leave with fully charged batteries.

Fig. 4(c) shows the probability distribution of SoCs at the point of departure of EVs from the parking lot while Fig. 4(d) shows the cumulative probability distribution of the same. Over the entire year, about half of the vehicles (51%) leave fully charged whereas the rest leave at lower states of charge. However, even among these EVs where the batteries are not fully charged, most vehicles depart with high states of charge.

Over the entire year, a relatively small fraction of vehicles leave with inadequate charge. As shown in Table 2, about 20% of EVs depart with SoCs lower than 60% while about 3% of EVs depart with SoCs lower than 40% over the entire year. These EVs may not have sufficient range for future trips - a situation to be avoided for a commercial park and charge facility. As Fig. 4(b) shows, the vast majority of events where EVs departed with inadequate charge are in winter. As such, we further investigate this adequacy during the periods when the system performance is lowest - the worst month in the year.

3.3. Critical month analysis

The PV system is expected to meet the load across the whole year with varying irradiance and loads. In order to ensure that the system works satisfactorily across all conditions, we analyse the performance of the system during the month over which the system has its worst performance: the critical month. We choose the critical month as the month with the largest number of EVs leaving at SoC lower than 40%. This is found to be the month of December, primarily as a result of low irradiance.

Fig. 5(a) shows the distribution of SoCs of vehicles departing from the parking lot in December. Very few EVs are charged to SoCs over 80% and no EVs are fully charged. Most vehicles are charged to the 40–70% SoC range. This distribution is quite different to the distribution seen over the entire year in Fig. 4, where a large share of vehicles are fully charged. Fig. 5(b) shows the cumulative distribution of SoCs on departure while Table 2 shows the difference between the annual distributions and the critical month, December.

63% of EVs in December are found to depart at an SoC lower than 60% while 11% of EVs depart with an SoC lower than 40%. The share of vehicles leaving with inadequate charge is significantly higher in December than over the entire year. Since our objective is to reduce or eliminate the number of vehicles which depart at states of charge which may be considered inadequate by users, we focus on these vehicles. Some methods to raise the SoCs at exit of these vehicles are proposed and investigated in the following sections.

3.4. Increasing the adequacy of charging

We consider two methods to increase the adequacy of charging to these vehicles:

[3] about 24% of generated energy is curtailed, seen in yellow in Fig. 4(a).

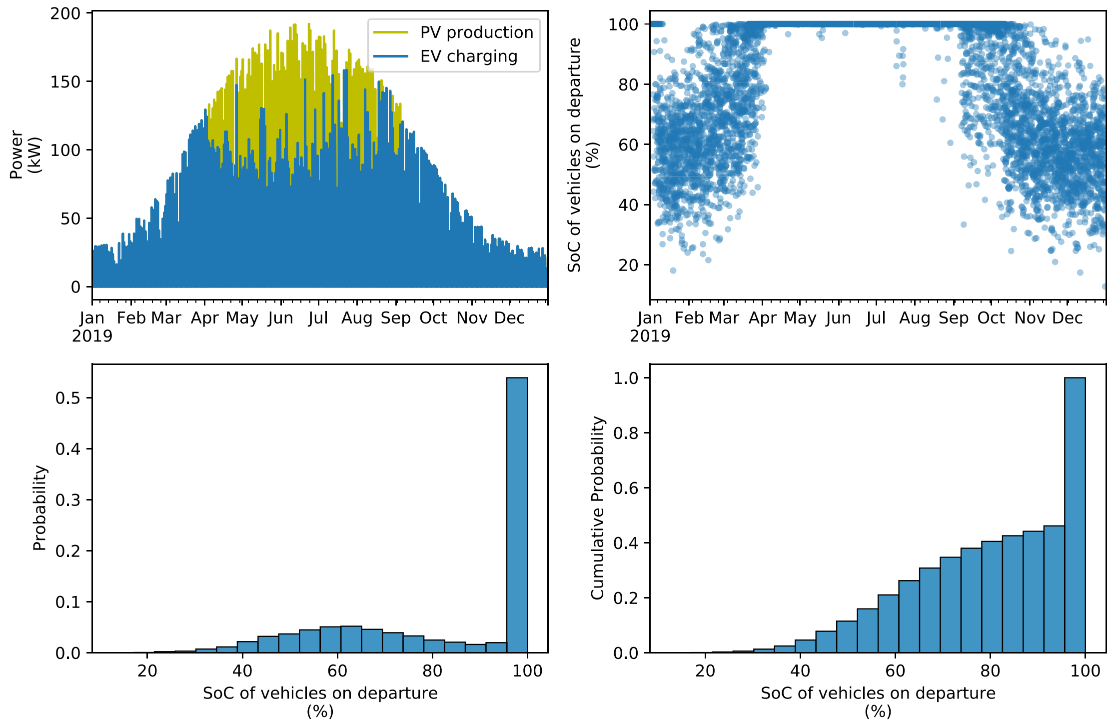


Fig. 4. (a) Solar power generation and off-grid EV charging over the year (b) SoCs on departure of EV charging at the solar parking lot over the year (c) Distribution of SoCs on departure and (d) Cumulative distribution of SoCs on departure.

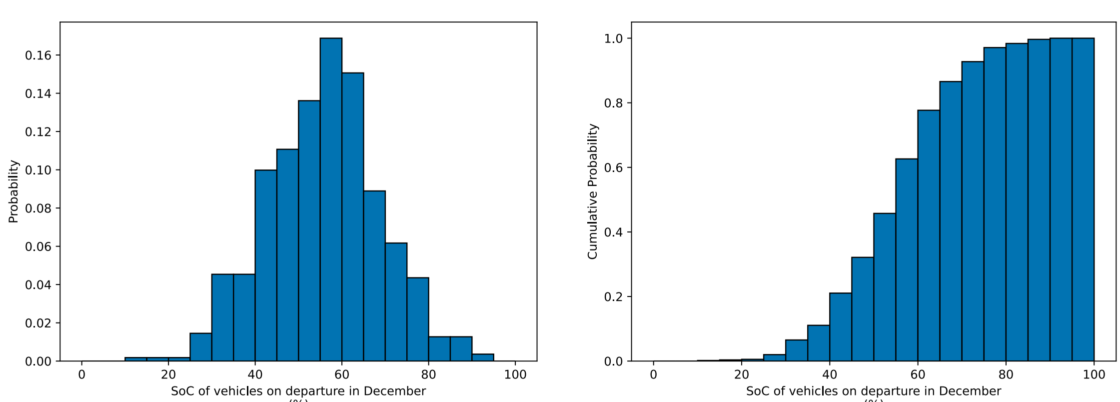
Table 2
Cumulative distribution of vehicles based on SoC at departure: comparison of annual case and critical month case.

State of Charge at departure	Fraction of EVs	
	Annual	December
<99%	49%	100%
<80%	39%	97%
<60%	20%	63%
<40%	3%	11%

1. Increasing the solar production in winter through the use of higher efficiency solar modules
2. Increasing the minimum duration time for which vehicles are permitted to use the parking lot

3.4.1. Increasing the solar production

The base scenario described in section 3.2 makes use of 320 Wp solar modules with about 19% efficiency, around the higher end of commercially used modules. However, commercial projects in



(a) Distribution of SoCs on departure of EV charging at the solar parking lot in December

(b) Cumulative distribution of SoCs on departure in December

Fig. 5. Distributions of SoCs on departure in December.

recent years have seen the application of increasingly efficient solar modules [41]. We analyse the effects of the use of higher efficiency solar modules at the design stage on the system performance. Laboratory tests measuring module level efficiency current report values as high as 24.4% for monocrystalline silicon [41]. As such, we investigate efficiencies ranging from the value chosen in the base case, 19%, to 24%, where modules which are commercially deployed in the future approach today's laboratory-measured efficiencies.

As before, the system performance is analysed based on the distribution of EVs by their SoC at departure. The results are shown in Fig. 6, where the fraction of EVs departing with SoCs below 40% and 60% are plotted as a function of increasing solar module efficiency.

As seen in Fig. 6, the fraction of vehicles which leave at states of charge below 60% reduce to some extent but those leaving with SoCs below 40% are relatively unaffected. As such, the improvement in adequacy of charging is very limited since the vehicles in critical need of charging do not receive it. The likely reason is that although the efficiency of energy conversion by the modules is higher, the available resource i.e. the irradiance levels in winter are not enough to generate the required electricity to adequately charge the plugged in vehicles.

3.4.2. Increasing the minimum parking duration

In the base case, the minimum duration of time that vehicles needed to be parked in order to be assigned to the long-term parking lot rather than the short term lot was 24 hours. As discussed in section 2.4, vehicles in large parking lots are generally divided based on their duration of stay into short term, long-term, meet and greet, etc. The minimum duration for a vehicle to be assigned to long-term parking lots can be as low as 8 hours, as in Beijing Airport, China [42], to as long as 5 days, as in Manchester Airport, UK [43].

Here, we investigate the effects of increasing this limit, which can be achieved through a relatively easily implemented change in parking lot policy. By increasing the minimum parking duration, the vehicles within the long-term parking lot would, on average, spend longer times plugged in, allowing them more time, and correspondingly more sun hours, to charge. We increase the minimum duration of parking in steps of one day. The occupancy of the parking lot was retained at similar levels - over 80% of the spaces were generally occupied by vehicles. This means that the revenue due to parking fees at the parking lot would remain unaffected, since the parking revenue is linked to occupancy of the parking lot. The results are shown in Fig. 7.

Fig. 7 shows that the shares of vehicles leaving with SoCs lower than 60% and lower than 40% are both found to reduce, though they are not eliminated, as a result of increasing the minimum parking duration. This is thus a more effective strategy at reducing the fraction of vehicles leaving at a low SoC than increasing the PV module efficiency.

However, given the same number of parking spaces, with vehicles staying longer, the total number of vehicles using the parking space reduces (shown in gray in Fig. 7). The case with a minimum duration of 5 days offers parking for only about 60% of the vehicles as the original case. Such an approach thus reduces the number of vehicles for whom the limited parking spaces can provide charging. Further, as can be seen in Fig. 3(a) a large number of vehicles visiting long-term parking lots park their vehicles for periods between 1 and 5 days. Thus such an approach reduces the fraction of visitors to the facility which can use this particular parking lot. A reduction in the number of vehicles results in a corresponding reduction in the total load as well. This leads to a higher share of curtailed energy.

Both the use of higher PV module efficiency and increasing the minimum duration of stay at the parking lot have limitations in terms of their effectiveness at increasing the adequacy of charging provided. In order to further increase the adequacy of charging provided by the system, in the next section, we investigate distributing the available energy differently among the plugged in vehicles.

4. Prioritised charging of vehicles

A fraction of vehicles plugged-in at the off-grid solar parking lot do not receive adequate charging in winter. We now try to allocate the available energy differently among the charged vehicles. The broad idea behind this approach is that vehicles with critically low SoCs need energy more than those with relatively high SoCs. Assigning a priority to the vehicles within the parking lot then enables charging of certain cars faster than others. We identify three strategies to do this:

1. 80% SoC sufficiency

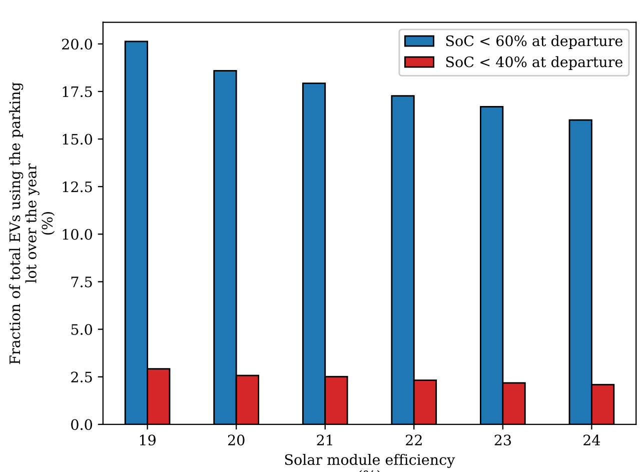


Fig. 6. Reduction in fraction of EVs leaving at inadequate states of charge due to increase in PV module efficiency.

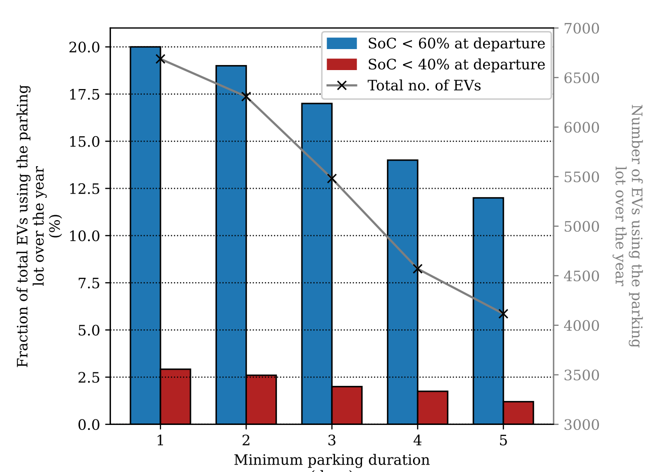


Fig. 7. Reduction in fraction of EVs leaving at inadequate states of charge due to increase in minimum parking duration.

2. Lowest SoC priority
3. Lowest Critical Ratio priority

The formulation of these strategies is initially described, after which they are compared with each other as well as the base case.

4.1. Formulation of priority based strategies

In each of the strategies, we distribute the available electricity among the plugged in vehicles based on a different rule. The first two strategies require data related to the plugged in EV's SoC to be known by the centralised system controller, as is possible with direct current (DC) charge points. The final strategy further requires the parking schedule of the vehicles to be known by the system. These strategies are described below:

4.1.1. 80% SoC sufficiency formulation

Here, we assume that it is of primary importance to charge all vehicles to 80% SoC, a value beyond which further charging is of lower priority. Retaining the earlier notation, at any given timestep, n, the State of Charge (SoC) of the i^{th} vehicle is $S_{i,n}$. Of the I_n vehicles plugged in at the timestep, n, the SoCs of the vehicles are in the set $\overline{B_n}$. A subset of $\overline{B_n}$ with $I_n^{SoC<80}$ elements includes all the values in $\overline{B_n}$ which are lower than 80. The elements of this subset are $\overline{B_n^{SoC<80}}$ and the identities of the corresponding vehicles are in $\overline{I_n^{SoC<80}}$. The power consumed by this section of the EV fleet depends on the available PV power in the n^{th} timestep, P_n^{PV} as

$$P_n^{fleet=\overline{I_n^{SoC<80}}} = \sum_{i\in\overline{I_n^{SoC<80}}} P_{i,n} \quad = minimum\left(P_n^{PV}, \sum_{i\in\overline{I_n^{SoC<80}}} c_{i,n}\right) \tag{4}$$

Thus, the power charged to the i^{th} connected vehicle is

$$P_{i,n} = \begin{cases} c_{i,n}, & P_n^{fleet=\overline{I_n^{SoC<80}}} \le P_n^{PV} \\ \dfrac{P_n^{PV}}{P_n^{fleet=\overline{I_n^{SoC<80}}}} \cdot c_{i,n}, & P_n^{fleet=\overline{I_n^{SoC<80}}} > P_n^{PV} \end{cases} \tag{5}$$

In case all vehicles are charged to 80%, then all the vehicles are charged with equal priority as described in 3.1.

4.1.2. Lowest SoC priority formulation

In this strategy, the objective is to prioritise the charging of vehicles with the lowest state of charge. As in the previous case, at any given timestep, n, the State of Charge (SoC) of the i^{th} vehicle is $S_{i,n}$. At any given timestep, n, let $\overline{B_n}$ be the set of all the states of charge of the I_n plugged in vehicles.

Thus,

$$\overline{B_n} = \underbrace{\{S_{i,n}\cdots\}}_{I_n \text{ terms}} \quad \forall\ i\in\overline{I_n} \tag{6}$$

where $\overline{I_n}$ is the set of I_n unique values of i at the timestep n, and I_n is the occupancy of the parking lot at timestep n.

We define $\left|\overline{B_n}\right|$ as the non-decreasing ordered set of elements in $\overline{B_n}$. Similarly, $\left|\overline{I_n}\right|$ is the ordered set of vehicles identities sorted in non-decreasing order of corresponding value from $\overline{B_n}$. The vehicle identities at each position in $\left|\overline{I_n}\right|$ thus match the corresponding state of charge in $\left|\overline{B_n}\right|$. Every element in the ordered is assigned a rank, k, which ranges from 1 to I_n.

We then distribute the solar power in the n^{th} timestep, P_n^{PV}, among the I_n plugged in EVs. If the solar power, P_n^{PV}, exceeds the limits of charging of the entire fleet, we charge as described in the first case in Eqn (5) . If not, system works as follows. The power delivered to the i^{th} vehicle which is at the k^{th} rank at the timestep n is denoted by $P_{i,k,n}$. The power delivered per vehicle is decided according to the rank as shown in Fig. 8.

The procedure to establish the ranks is repeated every hour, similar to the timestep of the simulation.

4.1.3. Lowest critical ratio priority formulation

The next strategy assumes knowledge of the vehicle departure schedule in addition to the state of charge. As parking spots are generally reserved through an online reservation portal, large parking lot operators would typically have access to this data. Thus, vehicles which are due to leave in a few hours are treated differently than those which will remain in the parking lot for days or weeks. The indicator used in this case to prioritise the allocation of energy is the critical ratio. We define the critical ratio as the ratio of time remaining till departure to the battery depth of discharge.

At any time step, n, the duration of time remaining before departure for the i^{th} vehicle is $t_i^{exit} - n$. The depth of discharge, d, (in percentage) of the i^{th} vehicle at any timestep, n, is calculated as:

$$d_{i,n} = 100 - S_{i,n} \tag{7}$$

where $S_{i,n}$ is the state of charge of the i^{th} vehicle at the n^{th} timestep.

The depth of discharge may be considered analogous to the work still to be performed. From $\overline{B_n}$, the set of states of charge of plugged in vehicles, we calculate the set of depths of discharge, $\overline{d_{i,n}}$, for each of the vehicles. The critical ratio of the i^{th} vehicle in the parking lot at the n^{th} timestep, $CR_{i,n}$, is the ratio of duration of time remaining before departure to the depth of discharge:

$$CR_{i,n} = \frac{t_i^{exit} - n}{d_{i,n}} \quad \forall\ i\in\overline{I_n} \tag{8}$$

A low critical ratio thus implies that the vehicle is due to leave shortly and has a high depth of discharge while a high critical ratio implies that the vehicle will remain parked for a long duration and has a low depth of discharge.

Let $\overline{\Omega_n}$ be the set of critical ratios of all the vehicles in the parking lot at the timestep n:

$$\overline{\Omega_n} = \underbrace{\{CR_{i,n}, \cdots\}}_{I_n \text{ terms}} \quad \forall\ i\in\overline{I_n} \tag{9}$$

Let $|\overline{\Omega_n}|$ be the non-decreasing ordered sequence of elements in $\overline{\Omega_n}$. Every element in the sequence is assigned a rank, k, which ranges from 1 to I_n.

We then distribute the power in the n^{th} timestep, P_n, among the I_n plugged-in EVs. The power delivered to the i^{th} vehicle which is at the k^{th} rank at the timestep n is denoted by $P_{i,k,n}$. The power delivered per vehicle is decided according to the rank k as shown in Fig. 8. As in the earlier cases, the procedure to establish the ranks is repeated every hour in the simulation.

4.2. Comparison of prioritised charging approaches

A year of system operation was then run with plugged-in EVs

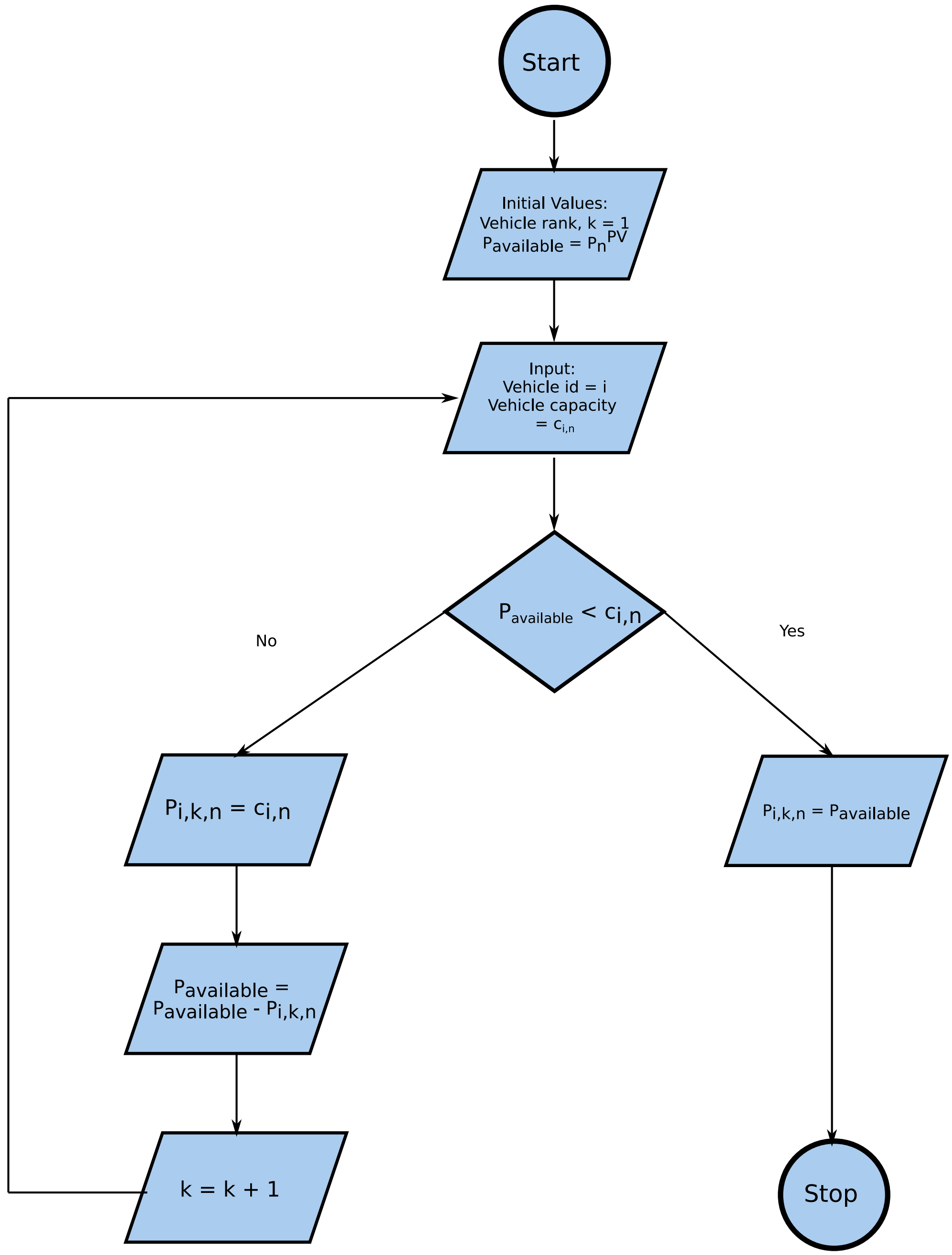


Fig. 8. Flow per timestep for allotting power among plugged in vehicles based on rank.

charged according to the three strategies:

1. 80% SoC sufficiency
2. Lowest SoC priority
3. Lowest Critical Ratio priority

We analyse the results by looking at the probability distribution of the states of charge on departure of EVs in each of the cases. These are shown in Fig. 9.

Fig. 9(a) shows the reference case: the distribution vehicles by the states of charge on departure in case of immediate charging of plugged in EVs. It is characterised by a large peak of fully charged vehicles with a smaller relatively flat distribution peaking around 60% SoC. With the 80% SoC sufficiency, as seen in Fig. 9(b), the rightmost peak is shifted to the left. Very few vehicles are fully charged and a small fraction is charged to an SOC higher than 80%. The majority of vehicles are charged to between 60 and 80%. A relatively low influence is seen on vehicles leaving with SoCs lower than 60% - the distribution is similar to the base case.

In Fig. 9(c), where the distribution of SoCs on departure are shown with the lowest SoC priority rule, the number of fully charged vehicles is found to reduce slightly. The spread of the distribution of vehicles leaving at lower SoCs is reduced, with the peak shifting slightly leftward. A noticeable difference is the near elimination of vehicles leaving at SoCs lower than 40% with the fraction dropping to 0.03% of the total fleet. The share leaving with SoC below 60% remains relatively unchanged, but almost all these vehicles have over 50% SoC.

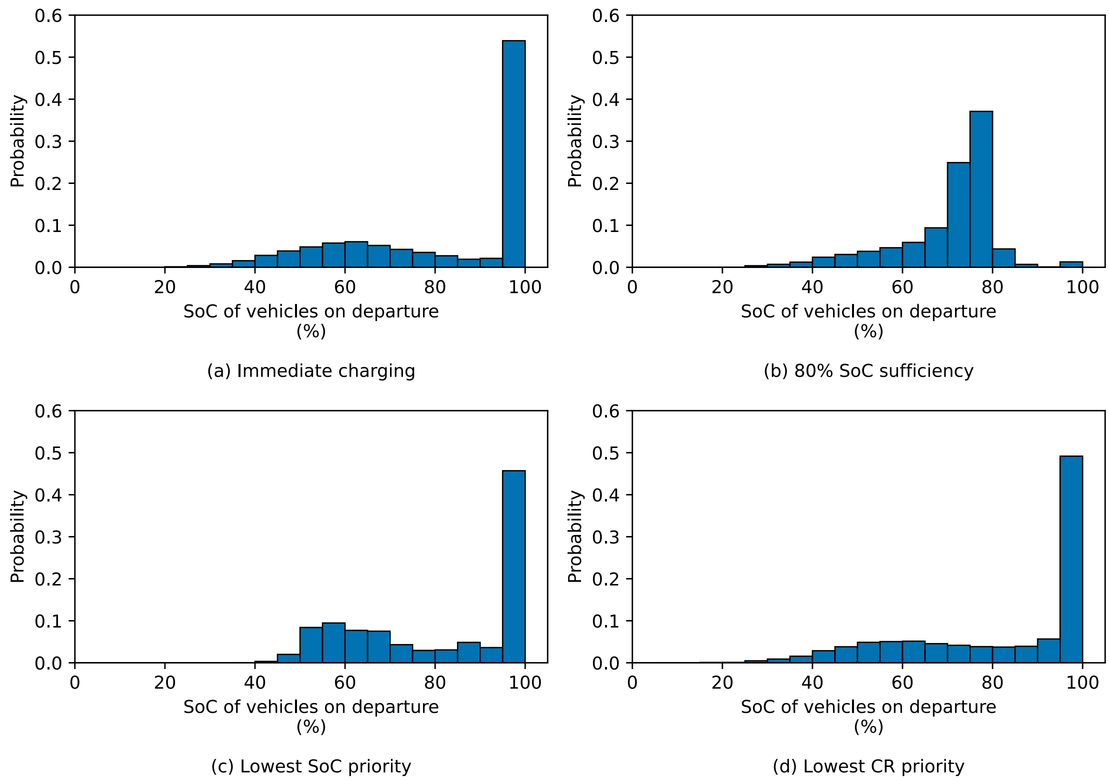


Fig. 9. Histograms of SoC of EVs on departure in case of a) Immediate charging, b) 80% SoC sufficiency, c) Lowest SoC priority and d) Lowest Critical Ratio priority.

Finally, in Fig. 9(d), the case with the prioritisation of charging of vehicles with the lowest critical ratio is seen. This is found to lead primarily to an increase in the share of vehicles leaving with SoCs between 80 and 100%, with a slight reduction in the number of vehicles which are fully charged relative to the base case. There is no notable influence on the vehicles leaving with SoC lower than 60%. An investigation of the distribution of critical ratios over the plugged in fleet at individual timesteps revealed that vehicles at higher SoCs which were nearing the time of departure often had lower critical ratios than those at lower SoCs with more time left, and thus took precedence in charging priority.

As in section 3.4, we now focus on the vehicles at relatively low states of charge, shown in Fig. 10.

As seen in Fig. 10, the 80% sufficiency strategy results in a reduction in the share of vehicles leaving with SoCs lower than 60% but has little effect on those leaving with SoCs lower than 40%, which are in critical need of charging. In contrast, the lowest SoC prioritising strategy effectively ensures charging to the vehicles which are in critical need of charging. The critical ratio strategy is seen to have a very low influence on the vehicles departing with low SoCs relative to the base case. The additional inclusion of the departure schedule in the strategy thus brings no added value. For a system aiming to reduce or eliminate the number of vehicles which depart at the lowest states of charge, the strategy prioritising charging of the lowest SoC is therefore recommended.

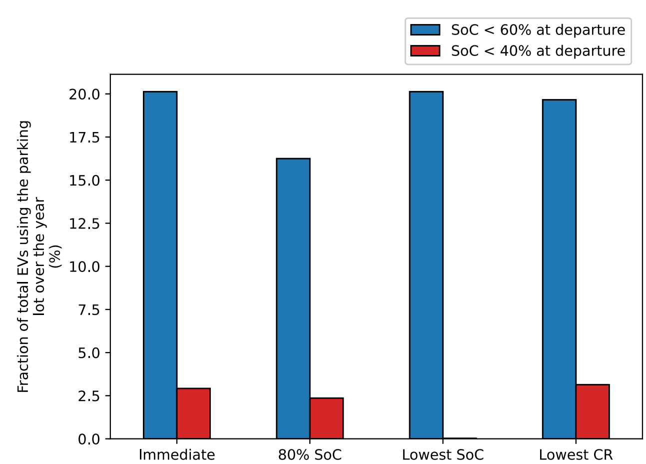
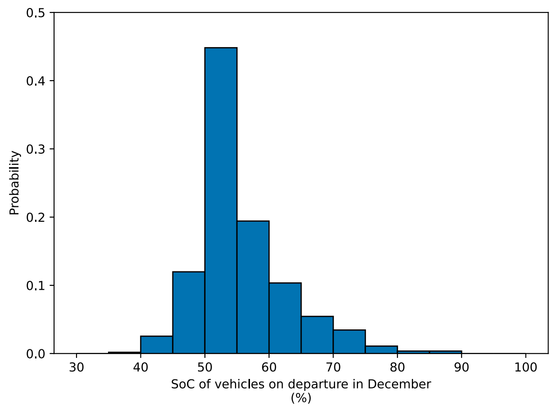


Fig. 10. Comparison of energy allocation strategies on the fraction of EVs leaving at inadequate states of charge.

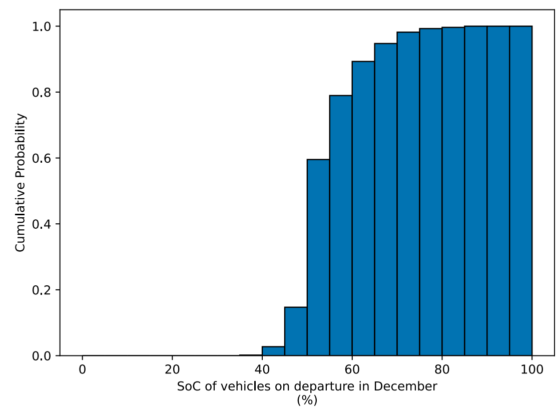
4.3. Critical month analysis with the lowest SoC priority strategy

The performance of the system in terms of adequacy of charging provided during the critical month, December, was of particular concern, as described in section 3.3. Having identified the best strategy for allocation of available energy (lowest SoC priority), we now analyse the performance of the system in the critical month while using this strategy. The distribution of SoCs of EVs at departure in December under the lowest SoC priority strategy are shown in Fig. 11(a) while Fig. 11(b) shows the cumulative distribution.

As seen in Fig. 11, nearly all vehicles depart with SoCs between 40% and 80%. No EVs are fully charged and a very small fraction - 0.2% leave with an SoC lower than 40%. Table 3 compares these results with those from December in the base case. A majority of EVs (79%) still leave with an SoC lower than 60%. This suggests that



(a) Distribution of SoCs on departure of EV charging at the solar parking lot in December



(b) Cumulative distribution of SoCs on departure in December

Fig. 11. Distributions of SoCs on departure in December under lowest SoC priority charging.

the performance of the system during the critical month remains a challenge.

4.4. Combined strategies

Finally, we analyse the performance of the system under a combination of the system design approaches described in section 3.4 as well as the prioritised charging strategies outlined in section 4.1. We use the approach with the best results in each case: increased minimum parking duration and lowest SoC priority based charging. As in earlier cases, we focus on the EVs leaving at the lowest SoCs. The case with lowest SoC priority based charging is shown in Fig. 12(b) while Fig. 12(a) shows the immediate charging case for reference.

Fig. 12(b) shows the reduction in the share of EVs departing from the parking lot at states of charge lower than 40% and 60% with increasing minimum parking durations. The number of vehicles leaving with SoCs lower than 40% are seen to be nearly eliminated with one day as the minimum parking duration. Longer parking durations completely eliminate the vehicles departing with SoCs lower than 40% and also reduce the number of vehicles leaving at SoCs below 60%. Such a combined approach in system design would yield the best results in terms of adequate charging of EVs using the parking lot.

Although a majority of vehicles are not expected to be fully charged across all seasons, combining strategies effectively eliminates problem of vehicles leaving while still in critical need of charging.

4.5. Commercial application of off-grid solar parking lots for EV charging

At locations such as airports, parking lots are commercially operated, with paid parking offered as a service. The annual revenues from parking lots can be in the range of tens to hundreds of millions of USD for medium to large airports [44]. However, the costs of electrification for such large fleets (as many as several tens of thousands of vehicles at a time) can be correspondingly high, particularly due to the high peak capacity needed. Since the typical costs of electricity paid by EV drivers are relatively low, the pay back periods for EV charging infrastructure tend to be longer than for conventional paid parking.

With increased electrification of the fleet, range anxiety of EV drivers is expected to play a role in the parking choices of increasing numbers of visitors. Availability of EV charging infrastructure at the destination is known to have a significant role in the trip planning of EV drivers [45]. Locations with insufficient or inaccessible parking are likely to be avoided by BEV drivers, shifting them to other transportation modes or even different locations. Provision of accessible public EV charging infrastructure is an established method of reducing range anxiety [3]. Solutions such as the system proposed in this work can help achieve ubiquitous charging by offering lower cost pathways for electrification and alternatives for locations with constrained grid capacity.

Table 3
Cumulative distribution of vehicles based on SoC at departure in the worst month, December: comparison of the base case with immediate charging and lowest SoC priority strategy.

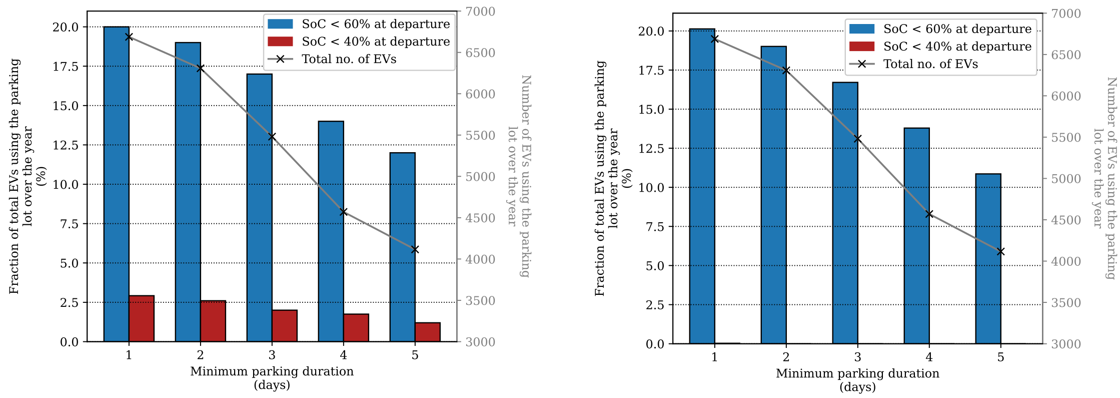
State of Charge at departure	Fraction of EVs in December	
	Base case	Lowest SoC Priority
<99%	100%	100%
<80%	97%	99%
<60%	63%	79%
<40%	11%	0.2%

5. Conclusions

In this study, we investigate the use of an off-grid solar photovoltaic system for the charging of electric vehicles at long-term parking lots. The effectiveness of the off-grid system is studied through analysis of the states of charges at departure of the EVs plugged in at the parking lot over the simulated year. With immediate charging, we find that about half of the vehicles leave with fully charged batteries, while the rest leave at lower states of charge. Over the year, about 20% of EVs depart with SoCs lower than 60% and about 3% with SoCs lower than 40%. These vehicles in particular are likely to have range issues for future trips. A high seasonal dependence is seen, with EVs leaving with lower SoCs mainly in winter.

Increasing the solar module efficiency had a marginal effect on the EVs leaving at the lowest SoCs. Increasing the minimum duration of stay of EVs at the parking lot was found to be more effective than increasing the module efficiency. There were limits to the effectiveness of these strategies since a fraction of EVs, albeit a small one, still departed with inadequate range.

The restriction of charging of vehicles to 80% SoC was found largely to reduce the number of fully charged vehicles, while the vehicles at lower SoCs were not greatly affected. The lowest SoC



(a) Immediate charging

(b) Lowest SoC strategy

Fig. 12. Reduction in fraction of EVs leaving at inadequate states of charge over the year due to increase in minimum parking duration: comparison of strategies.

formulation was found to be far more effective at reducing the number of vehicles leaving at lowest SoCs. The lowest critical ratio, which would require the additional integration of the arrival-departure schedule with the energy system, was found to have poorer results than the lowest SoC method. We therefore identify the lowest SoC priority rule to be most effective at increasing the adequacy of charging provided by the system to vehicles.

Although the lowest SoC priority effectively reduces the numbers of vehicles leaving at the lowest SoCs, the performance of the system in the worst months remains a challenge. Combining the lowest SoC priority rule with other measures can alleviate this issue to a certain degree, but this strategy does not achieve 100% or very high SoCs for most vehicles in the winter months. The results suggest that a relatively small size of grid connection, primarily for use in winter, may however be sufficient for adequate charging of vehicles in long-term parking lots at the location considered. This can result in significant reduction in project costs, though a financial estimation of this reduced cost remains out of scope of this work.

The insights from the results obtained here can be generalised to a certain extent for application in other locations. Although irradiation profiles are site specific, the location chosen in this work has a relatively high latitude of 51° North. At locations closer to the Equator with higher irradiance during the critical month, a larger share of vehicles are expected to leave with higher SoCs even in winter. For parking system operators, increasing the minimum parking duration for summer and reducing them in winter can effectively be used to reduce PV curtailment in summer while retaining high performance in winter. For long-term parking lots in remote locations which are used only in summer such as those at campsites or vacation homes, off-grid solar charging can be a viable design choice even at higher latitudes.

The methods used here can also provide insights for both system designers as well as for future researcher work. The analysis of SoCs of EVs on departure can be used as a measure of utilisation and successful placement of public charging stations. Currently such studies quantify the success of charging by measuring the average daily units of electricity consumed [18]. The various strategies analysed and compared here can all be applied in future system design. New priority formulations can also use data like the expected driving range per vehicle if such data is provided by the EV drivers.

Although off-grid solar charging at long-term parking locations is an interesting niche application, a more widespread concern is the charging of large groups of vehicles for shorter durations at locations with a constrained grid capacity. We aim to investigate charging at these locations in future works. Though similar to the off-grid case in terms of limits of available energy, the availability of (limited) grid capacity changes the constraints of the system. Adjustment of the times of charging are expected to have a greater role in those systems and will be investigated in future research. Also of interest is the value that the batteries of parked vehicles can provide to large solar parks, enabling them to expand the range of energy services these parks can provide, and thus their economic value.

Funding sources

This research work was supported by the European Funds for Regional Development through the Kansen voor West program grant 00113, for the project, Powerparking.

Author statement

Rishabh Ghotge – Conceptualisation, Writing- original draft, Methodology, Formal analysis, Software, Visualisation. Zofia Lukszo- Supervision, Writing – review and editing. Ad van Wijk – Supervision, Writing – review and editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank Yitzhak Snow for the data on parking patterns at Boston Airport. The authors also thank Edward Heath for interesting discussions on the topic.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.120356.

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